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Analysis

Titled Amazon Indigenous Communities Cut Forest Carbon Emissions

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ABSTRACT

Indigenous communities (ICs) have emerged as important players in global efforts to reduce forest carbon emissions, in part because they are viewed as conscientious stewards of the forest lands to which they have legal title. Yet ICs tend to be located in remote areas where deforestation would be limited regardless of who manages them. Therefore, to determine whether IC management actually cuts forest carbon emissions, it is important to control for such confounding factors. To that end, we use propensity score matching and regression to analyze the effects on 2001–2013 deforestation and forest carbon emissions of IC management in the Amazon regions of Bolivia, Brazil, Ecuador and Colombia. We find that IC management reduces both deforestation and forest carbon emissions in Bolivia, Brazil and Colombia. We are not able to discern a statistically significant effect in Ecuador. These findings suggest that IC management can, in fact, help combat climate change.

1. Introduction

Forest clearing and degradation contribute one-tenth to one-seventh of global greenhouse gas emissions, roughly the same amount as the transportation sector (Baccini et al., 2012; Harris et al., 2012; van der Werf et al., 2009). Over the past two decades, indigenous communities (ICs) have emerged as increasingly important players in efforts to address this problem (Schroeder, 2010; Wallbott, 2014). Associations such as the International Indigenous Peoples' Forum on Climate Change (IIPFCC) now represent ICs in climate negotiations. Media coverage regularly touts the benefits of IC forest carbon management (Popkin, 2015; Fogarty, 2014; Kahn, 2014). And the 2015 Paris Agreement establishing a post-2020 international climate policy architecture contains numerous references to ICs. For example, the agreement recognizes the need to “strengthen knowledge, technologies, practices and efforts of local communities and indigenous peoples related to addressing and responding to climate change” (Paris Agreement, 2016).

Recent research appears to support the contention that IC management can help stem forest carbon emissions. We now know that ICs have formal legal title to a significant portion of the world's forest carbon—one-fifth, by one recent estimate (MAPF, 2015). In addition, remote sensing data indicate that rates of deforestation inside legally recognized ICs (hereafter, simply ‘ICs’) tend to be significantly lower than rates outside (Oliveira et al., 2007; Nepstad et al., 2006; Stevens et al., 2014). For example, Stevens et al. (2014) find that between 2000 and 2012, deforestation rates inside ICs in the Brazilian Amazon were seven times lower than rates outside, and rates inside ICs in the Colombian Amazon were three times lower.

However, the fact that ICs contain considerable forest carbon and tend to have relatively low rates of deforestation is by no means proof that IC management causes significant reductions in forest carbon emissions. There are at least two reasons. One is that forests under IC management may have pre-existing geophysical and socioeconomic characteristics, such as location in remote, thinly populated areas, that are at least partly responsible for relatively low deforestation rates. A recent *Science Magazine* article neatly articulates this concern.

> [S]ome question whether data support indigenous communities' claims to be better forest carbon stewards than outsiders. One confounding factor … is that many remaining indigenous territories are in remote, humid tropical forests with low population densities, meaning that lack of development pressure, rather than effective management, may explain why such forests have remained standing. (Popkin, 2015)

A second reason is that on a conceptual level, it is not altogether clear what effect we should expect IC management to have on

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deforestation in any given geography.[1] Although there are certainly good reasons to expect IC management to reduce clearing, there also are good reasons to expect the opposite. As for the reasons to expect it to reduce deforestation, perhaps most important, IC management could in principle prevent a 'tragedy of the commons'—overexploitation due to ill-defined and insecure property rights (Hardin, 1968; Bromley, 1992). Research suggests that weak property rights can encourage land-poor households to colonize frontier areas (Clark, 2000; Oliveira, 2008), strengthen colonists' preferences for unsustainable productive activities with quick returns instead of investments in forests and other long-lived assets (Mendelsohn, 1994; Barbier and Burgess, 2001) and prevent land managers from participating in payments for environmental services and reducing emissions from deforestation and degradation (REDD) initiatives (Wunder, 2005; Gregersen et al., 2010). Forest management by local communities with formal legal title to their land could alleviate each of these problems.

But an equally plausible case can be made that IC management could spur forest cover change. Assigning property rights to entire communities instead of individual households can recreate common-pool resource problems on a local level, and communities vary considerably in their ability and willingness to successfully address these problems (Ostrom, 1990; Persha et al., 2011). Moreover, community control over forests can be undermined or co-opted by powerful private actors or by central governments (Johnson and Forsyth, 2002; Engel and López, 2008; Ribot et al., 2006). Finally, by improving communities' access to credit and/or extending their planning horizons, titling can raise the returns on agriculture relative to forests, thereby encouraging extensification (Liscow, 2013; Farzin, 1984).

Hence, empirical research using quasi-experimental methods that control for pre-existing land characteristics is needed to gauge whether and to what extent legally recognized IC management actually reduces forest cover change. A handful of studies, mostly published in the past five years, have begun to fill that gap. They use cross-sectional data and methods, in essence measuring the effect of IC management by comparing the rate of deforestation on land under IC management with the rate on land without it, controlling for observable land characteristics. Most of these studies find that on net, IC management stems deforestation. Relying on multinomial logit regression models, Muller et al. (2012) show that ICs in Bolivian lowlands inhibited deforestation between 1992 and 2004. Using matching, Vergara-Aseno and Potvin (2014) find that ICs in Panama cut deforestation between 1992 and 2008, although not by as much as strictly protected areas. Using regression models, Nelson et al. (2001) conclude that ICs in Darién, Panama, reduced deforestation between 1987 and 1997. Based on a matching analysis, Nolte et al. (2013) conclude that ICs in Brazil avoided significant deforestation between 2000 and 2005, particularly in places with high deforestation pressure. And using similar methods, Nelson and Chomitz (2011) find that protected areas under indigenous stewardship (not ICs per se) in Latin America reduced fire incidence, a proxy for deforestation, between 2000 and 2008. In contrast to these five studies, Pfaff et al. (2014) conclude from a matching analysis that ICs in Acre, Brazil, did not have a significant effect on forest loss between 2000 and 2008.[2]

The present study uses cross-sectional matching and regression along with fine-scale satellite data to examine the long-run effects on both deforestation and forest carbon emissions of IC management in the Amazon region of four countries: Bolivia, Brazil, Ecuador and Colombia. We find that after controlling observable confounding factors, IC management reduces deforestation and forest carbon emissions in Bolivia, Brazil and Colombia. We are not able to discern a statistically significant effect in Ecuador.

Our study makes three contributions. First, as noted above, it adds to the thin literature that uses quasi-experimental methods to evaluate the effect on deforestation of IC management, controlling for pre-existing land characteristics. Second, to our knowledge, it is the first to directly estimate the effect of IC management on forest carbon emissions as well as deforestation. And finally, to our knowledge, it is the first to examine the effects of IC management in multiple countries using consistent methods and data, ensuring that results are comparable across countries.[3]

2. Theory of Change

As noted above, the goal of our analysis is to identify the effect of legally recognized IC management—our 'treatment'—on deforestation and forest carbon emissions—our 'outcomes.' The treatment comprises two separable components: IC management and formal legal recognition of that management, which we refer to as titling. To underpin our empirical analysis and discussion of results, this subsection presents a set of hypotheses for potential causal pathways between (i) each of these two components of the treatment and (ii) our outcomes.

To keep the discussion manageable, we make two expositional simplifications. First, although our empirical analysis includes two outcomes—deforestation and forest carbon emissions—we focus only on deforestation. The reason is that the two outcomes are directly related: reductions in deforestation necessarily imply reductions in forest carbon emissions. Second, although as discussed in the Introduction, our treatments could in principle either reduce or exacerbate deforestation, given our empirical findings, we frame the theory of change as a set of hypotheses about how they might reduce it.

It is important to emphasize that these hypotheses are only meant to establish the range of plausible causal mechanisms that might explain a link between formal IC management and deforestation, and that identifying which mechanisms actually drive our results is beyond the reach of our data and beyond the scope of our analysis. Finally, we note that given the considerable differences in the institutional, geophysical and socioeconomic characteristics of our study countries (discussed in Section 3), causal mechanisms may well differ across countries and even within them.

2.1. IC Management

Here we consider the effect of IC management separate from formal

[1] This paragraph and the next are drawn from Blackman et al. (2014).

[2] A second, smaller group of studies—Blackman et al. (2017), Blackman (2018); Ben Yishay et al. (2017), Buntaine et al. (2015) and Hargrave and Kis-Katos (2012)—uses panel data and methods to examine the link between ICs and deforestation. However, these studies measure effects that although related, are different from the one our study (along with the other cross-sectional studies just noted) measures in two important ways. First, our study aims to measure the effects on deforestation of both (i) IC management and (ii) formal legal recognition of that management. It does that by, in essence, comparing the rate of deforestation on land that has both (i) and (ii) with the rate on land that has neither (i) nor (ii), controlling for land characteristics. The aforementioned panel data studies, by contrast, measure only the effect of formal legal

(*footnote continued*)
recognition of pre-existing IC management. They do that by, in essence, comparing the rate of deforestation on land that has both (i) and (ii) with the rate on land that has (i) but not (ii), again controlling for land characteristics. Second, in general, cross-sectional studies like ours measure long-run effects while panel data studies measure short-run effects (Houthakker, 1965; Egger and Pfaffermayr, 2005). Hence, our study examines the long-run effects of legally recognized IC management whereas panel data studies examine the short-run effects of providing legal title for land already under IC management.

[3] To our knowledge, Nelson and Chomitz (2011) is the only other quasi-experimental study that examines effects of IC management on forests in multiple countries. However, that paper only measures the effects of protected areas under indigenous stewardship, not ICs per se, examines effects on fire incidence, not forest cover change or forest carbon emissions, and does not disaggregate results by country.

legal recognition of that management. We describe potential causal pathways related to internal governance, external governance and attitudes regarding conservation.

2.1.1. Internal Governance

Management and oversight of forest cover change in developing countries' forests are frequently weak for a variety of well-known reasons, including ill-defined property rights in forested areas, logistical challenges associated with transportation and communications, and shortages of political will, regulatory manpower and funding (Seymour and Busch, 2016; Chomitz, 2007). Therefore, as discussed in the Introduction, forests can be quasi open-access regimes susceptible to overexploitation. In principle, IC management, even if not legally recognized, can help mitigate that problem. Given proper conditions and incentives, local communities have the capacity to sustainably manage forests (Sheil et al., 2015; Persha et al., 2011; Rustagi et al., 2010; Ostrom, 1990). Also, ICs may favor agricultural and forest management technologies that are relatively environmentally benign. For example, they may engage in small-scale subsistence agriculture and forest extraction, rather than commercial operations (Toledo, 2001; Berkes and Folke, 2000).

2.1.2. External Governance

State agencies and civil society may take active measures to promote forest conservation in ICs even if these communities do not have legal title to their land. For example, as discussed in the next section, Brazil's second (1891) constitution mandated the protection of 'Indian' communities and traditional lands which did not have formal legal title to their land, and led to the creation of a series of government institutions that aimed to fulfil that mandate (Ben Yishay et al., 2017; Ortiga, 2004).

2.1.3. Conservation Attitudes

Finally, in principle, IC members and leaders may place more value on forest conservation than other types of land managers. There are at least three related reasons. One is that ICs' extended engagement with the forests they have historically controlled may give rise to longer planning horizons, which facilitate sustainable management (Mendelsohn, 1994; Barbier and Burgess, 2001). In addition, some research suggests that forests—and nature more generally—are central to ICs' cosmology and ethnic identity (Toledo, 2001; Berkes, 1999; Eisenstadt and West, 2017). Finally, ICs may be more dependent on the ecosystem services provided by forests—including provisioning, regulating, supporting and cultural—than other forest managers (MEA, 2005; Toledo, 2001).

2.2. Titling[4]

Here we consider the effect of formal legal recognition of IC forest rights, or titling, on deforestation. We describe potential causal pathways related to internal governance, external governance, external interactions and livelihoods. It is important to emphasize at the outset that the titling in question is collective rather than individual, that is, land rights are awarded to the IC as a whole rather than to households or individuals that belong to the IC.

2.2.1. Internal Governance

Titling typically entails three activities: the community must convene internal meetings to decide whether and how to participate and be represented in the titling process; it must meet with external stakeholders, including representatives of government titling agencies and NGOs; and the boundaries of the community must be physically and digitally demarcated (Blackman et al., 2017; Ortiga, 2004). All three activities could theoretically enhance ICs' internal forest governance: territorial demarcation could focus scarce community governance resources on a particular forest area; meetings of community members could help promote dialogue and consensus on more effective forest management; and meetings between community representatives and external stakeholders could help build community governance capacity.

2.2.2. External Governance

Titling could enhance pressure to stem deforestation exerted by state entities such as regulators and non-state entities such as environmental NGOs. It could do that by making it easier for these agents to assign culpability for such activities to the community that is legally responsible for managing it, and by making it easier for ICs to register formal complaints with regulators about encroachment on their lands (Stevens et al., 2014; Hayes, 2007; Schwartzman and Zimmerman, 2005).

2.2.3. External Interactions

Titling could facilitate ICs' interactions with external agents (other than those directly involved in monitoring forest cover change), which in turn could reduce deforestation. For example, tilting could make ICs eligible to participate in government programs that provide technical assistance to forest managers (Stevens et al., 2014). Titling also could ratchet up ICs' interactions with private sector entities such input providers, which in turn could reduce forest cover change. For example, tilting could make it easier for communities to obtain technical assistance for investments in intensive agriculture or improved silviculture.

2.2.4. Livelihoods

Finally, in principal, titling could enhance ICs' livelihoods, which in turn could reduce forest cover change (Ding et al., 2016). Titling could boost livelihoods as a result of the two factors discussed above: internal governance and external interactions. Each could have both a direct effect on forest cover change and an indirect effect via livelihoods. For example, titling could enhance internal governance, which could directly reduce forest cover change. And titling could also boost communities' livelihoods (by, for example, more efficiently allocating public investment resources), which in turn could indirectly cut forest cover change (by, for example, reducing communities' reliance on shifting agriculture and timber). Of course, the relationship between livelihoods and deforestation is complex, and in some cases, enhanced livelihoods actually spur forest cover change (Chomitz, 2007). Still, the opposite effect is at least possible.

3. Background

This section provides brief background on the geophysical and institutional characteristics of our study countries—in particular, their indigenous populations, ICs, forests, and climate strategies. We preface summaries for each country with a brief discussion of the *de jure* rights enjoyed by ICs with legal title because these rights are surprisingly similar in all four countries. In principle, formal legal title can confer seven types of rights (Stevens et al., 2014):

- access: the right to enter or pass through a community area;
- withdrawal: the right to harvest timber and non-timber forest products;
- management: the right to make decisions about forest resources and territory for which the community has access and withdrawal rights;
- exclusion: the right to refuse access to and use of the forest;
- due process and compensation: the right to legally challenge a government's efforts to take one, several or all of the community's forest rights;
- alienation: the right to transfer property to another entity; and
- unlimited duration: the ability to exercise rights over an unlimited period of time.

[4] This section draws from Blackman et al. (2017).

Table 1
Study country characteristics.

Variable	Data source	Bolivia	Brazil	Colombia	Ecuador
Population					
Population (millions 2016)	World Bank (2018)	10.9	207.7	48.7	16.4
% indigenous (2010)	World Bank (2015)	41.0	0.5	3.3	7.0
No. indigenous peoples (2014)	World Bank (2015)	114	241	83	32
No. indigenous languages (2014)	World Bank (2015)	33	186	65	13
% indigenous people in rural areas (2005–2012)	World Bank (2015)	52	71	78	79
Territory					
National territory (millions ha 2017)	World Bank (2018)	108.3	835.8	111.0	24.8
Amazon region (millions ha 2016)	Mayorga et al. (2012)	67.3	509.4	49.6	11.6
IC land in Amazon region (mil. ha 2016)	LandMark (2016); Mayorga et al. (2012)	11.0	111.2	26.8	6.3
No. ICs in Amazon region (2016)	LandMark (2016); Mayorga et al. (2012)	293	584	205	64
IC rights[a]	Stevens et al. (2014)				
Conferred by award title					
Access		Yes	Yes	Yes	Yes
Withdrawal: timber		Yes	Yes	Yes	Yes
Withdrawal: NTFPs		Yes	Yes	Yes	Yes
Management		Yes	Yes	Yes	Yes
Exclusion		Yes	Yes	Yes	Yes
Due process		Yes	Yes	Yes	No
Alienation		No	No	No	No
Unlimited duration		Yes	Yes	Yes	Yes
Government action on IC rights	Stevens et al. (2014)	Positive	Positive	Negative	Negative
Drivers of deforestation (%, 1990–2005)[b]	de Sy et al. (2015)				
Mixed agriculture		0	1	13	n/a
Smallholder crop agriculture		5	0	11	n/a
Commercial crop agriculture		27	10	0	n/a
Tree crops		0	1	0	n/a
Pasture		39	82	62	n/a
Other		28	7	15	n/a
Climate	CIAT (2018)				
GHG emissions (2014 MtCO2e)		134.2	1357.2	182.4	94.5
LULUCF GHG emissions (2014% total)		64	23	11	36
NDC overall GHG target		n/a	37% ↓ 2005 levels by 2025	20% ↓ BAU by 2030	20.4–25% ↓ BAU by 2025 in energy sector
NDC LULUCF targets deforestation		Zero illegal deforestation by 2020; 54 mil. ha net forest coverage in 2030	Zero illegal deforestation by 2030	None	None

BAU = business as usual; GHG = greenhouse gas; IC = indigenous community; LULUCF = land use, land use change and forestry.
[a] Stevens et al. (2014) define these rights as follows: access is the right to enter or pass through a forest area; withdrawal is the right to harvest timber and nontimber forest products; management is the right to make decisions about forest resources and territory for which the community has access and withdrawal rights; exclusion is the right to refuse access to and use of the forest; due process and compensation is the right to legally challenge a government's efforts to take one, several or all of the community's forest rights; alienation is the right to transfer property to another entity; and unlimited duration is unlimited time during which the community can exercise its rights.
[b] Percentage of total area deforested between 1990 and 2005 with the specified follow-up land use.

As Table 1 indicates, in all four of our study countries, the award of formal tile confers rights to access, withdrawal, management, exclusion, and unlimited duration, and in none of these countries does it confer rights to alienation. In three countries (Bolivia, Brazil and Colombia), it confers rights to due process. Government action in Bolivia and Brazil has tended to strengthen IC rights over time, while government action in Colombia and Ecuador has tended weaken it (Stevens et al., 2014).

In addition to the type of rights conferred to ICs by the award of collective land title, another commonality across our study countries is the historical evolution of the process by which those awards have taken place. In each case, indigenous groups were awarded some type of land rights prior to the 1990s through agrarian reforms or other initiatives. However, a firm legal foundation and process for the award of such rights was put in place only through constitutional reforms and/or major new legislation in the late 1980s (in Brazil) or 1990s (in the other study countries).

3.1. Bolivia

Forty-one percent of Bolivia's population of 11 million is indigenous, by far the highest percentage of our four study countries (Table 1). This segment of the population includes 114 distinct peoples and 33 linguistic groups. Just over half of Bolivia's indigenous people live in rural areas, mostly in the Amazon region. This region comprises 67 million hectares, more than two-thirds of the country's total land

mass. Nationwide, the most important identifiable proximate drivers of deforestation (land uses that directly follow deforestation) are pasture (39%) and commercial crop agriculture (27%).

Although agrarian reforms starting as early as the 1950s awarded indigenous groups some land rights, large-scale provision of formal legal land title to ICs is a fairly recent phenomenon. Two legislative initiatives facilitated it. The first was Law 1715 of 1996, which created the National Institute for Agrarian Reform (INRA) and tasked it with resolving the country's outstanding land reform and land tenure issues by 2006. This law also created a framework for titling Original Community Lands, later reclassified as Indigenous Native Peasant Territories. Law 3545 of 2007 amended Law 1715. It was largely a reaction to INRA's failure to fulfil its mandate of resolving outstanding land tenure issues by 2006. It also reflected the 2006 election of Evo Morales, the country's first indigenous president. Law 3545's emphasis on indigenous land rights was unmistakable. It stipulated that all land belonging to the state be redistributed 'in favor of native, peasant and indigenous communities that do not have any or enough land.' As a result of these initiatives, > 350 ICs have received formal title to their land since 1999; 293 of these ICs, accounting for a total of 11 million hectares, are in the Amazon region.

In 2014, fully 64% of Bolivia's greenhouse gas emissions (134 million metric tons, MMT, of carbon dioxide equivalent, CO_2e) came from land use, land use change and forestry (LULUFC), by far the highest percentage among our four study countries, and a reflection of rampant forest cover change (detailed in Section 4). Bolivia's nationally determined contribution (NDC), submitted in accordance with the Paris Agreement, did not set a quantitative overall emissions reduction target. However, it did set quantitative goals for LULUFC: zero illegal deforestation by 2020 and a total of 54 million hectares net forest coverage in 2030.

3.2. Brazil

Less than 1% of Brazil's population of 208 million is classified as indigenous (Table 1). This segment of the population is diverse, however, consisting of 241 distinct peoples and 186 linguistic groups. More than two-thirds of Brazil's indigenous people live in rural areas, principally in the Amazon region. Among South American countries, Brazil's Amazon region is the largest, comprising a total of 509 million hectares. The most important proximate drivers of deforestation are pasture (82%) and commercial crop agriculture (10%).

In Brazil, the state has a long history of interaction with indigenous peoples (Ben Yishay et al., 2017; Ortiga, 2004). The country's second (1891) constitution mandated the protection of 'Indian' communities and traditional lands and led to the creation of a series of institutions assigned responsibility for fulfilling that mandate, the most recent being the National Indian Foundation (FUNAI), established 1968. By the 1980s, indigenous lands accounted for 18% of the Amazon region. However, these lands lacked formal title. Brazil's 1988 constitution stipulated that 532 recognized indigenous lands be demarcated and formally titled within five years. Although FUNAI was able to complete only about half of this job by the five-year deadline, today 584 ICs comprising > 111 million hectares in the Amazon region have received formal title, by far the largest cumulative IC territory among our four study countries.

In 2014, almost a quarter of Brazil's greenhouse gas emissions (1357 MMT CO_2e) came from LULUFC. Brazil's NDC goals include reducing overall emissions by 37% below 2005 levels by 2025 and achieving zero illegal deforestation by 2030.

3.3. Colombia

Just over 3% of Colombia's population of 49 million is classified as indigenous (Table 1). This segment of the population includes 83 distinct peoples and 65 linguistic groups. More than three-quarters of these people live in rural areas, mostly in the Andean and Savannah regions of the country, not the Amazon. Colombia's Amazon region comprises about half of its national territory. The principal identifiable proximate drivers of deforestation in Colombia are pasture (62%) and mixed agriculture (13%).

Colombia's 1961 agrarian reform created a legal framework for titling indigenous lands: it recognized the need to set aside indigenous lands as reserves (*resguardos*), a concept borrowed from Spanish colonial law (Ortiga, 2004). The first such reserves were established in the 1980s. The 1991 constitution created a new designation, Indigenous Territorial Entities. Today, a total of 205 ICs comprising almost 27 million hectares have been established in the Colombian Amazon.

In 2014, 11% of Colombia's total greenhouse gas emissions (183 MMT CO_2e) were from LULUFC. The country's NDC goal is reducing these emissions by 20% below business as usual by 2030, but there is no specific goal for emissions from LULUFC.

3.4. Ecuador

Seven percent of Ecuador's population of 16 million is indigenous (Table 1). This segment of the population is the least diverse among our four study countries: it includes 32 distinct peoples and 13 linguistic groups. Almost 80% live in rural areas, mostly outside the Amazon region, which constitutes about half of Ecuador's national territory.

As in Bolivia and Colombia, agrarian reforms awarded some lands to indigenous groups before a clear legal foundation and process were established in the 1990s (Ortiga, 2004). These awards were often made ad hoc to various individuals and institutions representing ICs. The 1998 constitution explicitly recognized the need to grant collective land rights to indigenous groups and led to the establishment of the Indigenous People and Afro-Ecuadorian Development Project and the National Indigenous and Afro-Ecuadorian Development Planning Council, a ministry-level agency, both of which aimed at provide ICs with secure land titles. Today, 64 ICs comprising 6.3 million hectares have been established in the Ecuadorian Amazon.

In 2014, more than a third of Ecuador's total greenhouse gas emissions (95 MMT CO_2e) were from LULUFC. The country's NDC only set a quantitative emission reduction goal for the energy sector: 20.4 to 25% reduction in emissions below business as usual by 2030, and did not set a specific goal for emissions from LULUFC.

4. Methods

Our analysis has two components: estimating avoided deforestation due to IC management and estimating avoided forest carbon emissions.

4.1. Deforestation

In measuring the effect of IC management on the rate of deforestation, the principal challenge we face is the usual one in impact evaluation: we do not observe the counterfactual—here, what the deforestation rate would have been absent IC management. A common solution is to use the contemporaneous deforestation rate on all land lacking IC management to proxy for the counterfactual. This amounts to estimating the effect of IC management as the simple difference between the deforestation rate inside and outside ICs. However, as discussed above, this approach is problematic because ICs tend to be disproportionately located on land with pre-existing geophysical and socioeconomic characteristics, such as distance to cities and population density, that affect deforestation. Therefore, this approach tends to conflate IC management's effects on deforestation with the effects of these confounding factors, thereby generating biased results.

To help control for such bias, following Andam et al. (2008) and Blackman et al. (2015), among others, we use a point-level matching approach. This approach entails three steps. First, we select a quasi-random sample of points (latitude and longitude coordinates) in our

study area. Next, for each point in a 'treated' area—that is, inside an IC—we find at least one point outside that is similar in terms of observable characteristics that affect deforestation. And finally, we measure the effect of ICs—the average treatment effect on the treated (ATT)—by comparing the average deforestation rate on the sample points inside ICs and the *matched* sample points outside.[5] The intuition for this approach is straightforward. Instead of using the deforestation rate on all land outside ICs as a proxy for the unobserved counterfactual, we use the rate only on land outside that is similar in terms of observable characteristics that drive deforestation.[6]

A variety of techniques can be used to match points inside and outside ICs and to compare outcomes on each subsample (Stuart, 2010; Caliendo and Kopeinig, 2008). To ensure robustness, we use three estimators.

4.1.1. Nearest Neighbor One-To-One Propensity Score Matching

The first estimator uses the propensity score as a univariate measure of the similarity between IC and non-IC points (Rosenbaum and Rubin, 1983). In the context of our study, a propensity score for a given sample point is the probability predicted by a probit regression that the point is 'treated'—that is, inside an IC—given its observed geophysical, socioeconomic and climatological characteristics. A propensity score can be interpreted as a weighted index of a point's observed characteristics, where the weights reflect the importance of each characteristic in explaining whether points are treated. Each IC point is matched to the one non-IC point with the closest propensity score. Matching is with replacement, so the same non-IC point can be matched to more than one IC point.

4.1.2. Nearest Neighbor One-To-Eight Propensity Score Matching

The second estimator uses propensity scores to match each IC point to the eight non-IC points with the closest propensity score, with the average outcome for these eight points serving as the counterfactual.

4.1.3. Probit With Matched Controls

The third estimator combines nearest neighbor one-to-one propensity score matching with regression, a hybrid approach that typically generates treatment effects estimates that are more accurate and more robust to misspecification than does either matching or regression alone (Imbens and Wooldridge, 2009; Ho et al., 2007). We estimate a point-level probit regression in which the sample is limited to points inside ICs and *matched* points outside, the dependent variable is a dummy variable that indicates whether a point was cleared between 2001 and 2013, the key independent variable is a dummy indicating whether the point was in an IC, and control variables are socioeconomic, geophysical and climatological point characteristics. Because matching is with replacement, we weight non-IC points that constitute the control group based on the number of times they were included as matches (Abadie and Imbens, 2006). The ATT is given by the marginal effect of the treatment dummy variable.

For each of these estimators, we require matched points outside ICs to be in the same biome as points inside. This 'exact' matching helps ensure that the two sets of points are similar in terms of unobserved features that affect deforestation. For all three matching estimators, we cluster standard errors at the second level of political administration (roughly the equivalent of counties in the United States) to help control for spatial correlation of errors.

For comparison's sake, in addition to the three matching estimators discussed above, we also use a 'naïve' estimator that does not control for confounding factors—the simple difference between the average rates of deforestation on all IC and non-IC points in our sample.

The reliability of matching estimators depends critically on the extent to which they are able to identify control units (points outside ICs) that are similar to treated units (points inside) (Stuart, 2010; Caliendo and Kopeinig, 2008). Following Rosenbaum and Rubin (1983), we use mean standardized bias (MSB) to assess 'matching quality.' MSB is the mean across our control variables of the variance-adjusted percentage difference between the mean for the IC subsample and the matched non-IC sample. Although a clear threshold for acceptable MSB does not exist, a statistic below 3 to 5% is generally viewed as sufficient (Caliendo and Kopeinig, 2008).

Finally, we use Rosenbaum bounds to check the sensitivity of our results to unobserved confounding factors for which our matching estimators do not control. The main identifying assumption for matching estimators, typically referred to as 'ignorability' or 'conditional independence,' is that we are able to observe and control for all important confounding factors that affect both selection into the treatment (in our case, location in an IC) and outcomes (deforestation between 2001 and 2013) (Stuart, 2010; Caliendo and Kopeinig, 2008). This assumption is untestable. In practice, we recognize that it may not hold. For example, stumpage values, which we do not observe, may be negatively correlated with location in ICs (if policy makers tend to shy away from titling communities in forests where logging earns particularly high profits) and positively correlated with deforestation (if loggers tend to target such forests). In principle, an inability to control for stumpage values could bias our treatment effects estimates upwards. We use Rosenbaum bounds to check the sensitivity of our results to this type of unobserved heterogeneity (Rosenbaum, 2002; Aakvik, 2001). Rosenbaum bounds indicate how strongly unobserved confounding factors would need to influence selection into the treatment in order to undermine a statistically significant ATT.

The Rosenbaum procedure adapted to a binary outcome generates a probability value for a Mantel and Haenszel (1959) test statistic for a series of values of Γ, an index of the strength of the influence that unobserved confounding factors have on the selection process. $\Gamma = 1$ implies that unobserved confounding factors have no influence, such that pairs of points matched on observables do not differ in their odds of being treated; $\Gamma = 2$ implies that matched pairs could differ in their odds of treatment by as much as a factor of two because of unobserved confounding factors; and so forth. The probability value on the Mantel and Haenszel statistic is a test of the null hypothesis of a zero ATT given unobserved confounding variables that have an effect given by Γ. So, for example, a probability value of 0.01 and a Γ of 1.2 indicate that ATT would still be significant at the 1% level even if matched pairs differed in their odds of being inside an IC by a factor of 1.2 because of unobserved confounding factors. We calculate Γ^*, the critical value of Γ at which ATT is no longer significant at the 10% level in each case where ATT is significant. An ATT estimate can be considered highly sensitive to unobserved heterogeneity when Γ^* is close to unity.

4.2. Forest Carbon Emissions

We estimate avoided forest carbon emissions as the difference between forest carbon emissions on all land inside ICs and emissions on counterfactual land outside. Estimating emissions inside ICs entails

[5] Blackman (2013) provides an introduction and practical guide to this approach.

[6] Panel data models are problematic in our case. To fit such models, the temporal variation in our treatment (the award of title) would need to overlap the temporal variation in our outcome (deforestation). As discussed below, our deforestation data (Hansen et al., 2013) begin in 2001. As a result, we could only use panel data methods to measure the deforestation effects of ICs that received title after 2001. However, < 10% of currently titled ICs in Colombia and < 25% in Brazil meet that criterion. In addition, titling dates for Ecuadorian ICs are not publicly available. Hence, estimating panel data models would necessitate dropping the vast majority of ICs in our study countries, an approach that would call into question the external validity of whatever findings we generated. As discussed above, our cross-sectional methods measure a different effect (the long-run effect of both IC management and legal recognition of that management) than would panel data methods (the short-run effect of legal recognition of pre-existing IC management).

three steps. First, we use global spatial data on tropical forest biomass (Saatchi et al., 2011) to calculate above-ground biomass (AGB) per hectare circa 2000 on sample points inside ICs that were cleared at some point between 2001 and 2013. To be conservative, we ignore below-ground biomass. Next, we estimate AGB on *all* land inside ICs that was cleared during this period by multiplying AGB for each cleared sample point by a factor that reflects the ratio of sampled hectares to total hectares. Finally, we estimate carbon dioxide emissions from this AGB using the conventional assumption that carbon comprises 50% of AGB(Larrea-Gallegos et al., 2017; Saatchi et al., 2011; Zarin et al., 2015) and then converting carbon to CO_2, using the standard factor of 3.67 based on the ratio of molecular weights of the two elements (Penman et al., 2003; Zarin et al., 2015). Hence, we assume all carbon from AGB is transferred to the atmosphere, recognizing that there can be significant lags associated with this transfer (Houghton et al., 2012; Ramankutty et al., 2007). We ignore methane emissions, again for the sake of being conservative. To summarize, we calculate

$$T = \sum_{i}^{n} (d_i \times A_i) \times 100$$

where i = an index of sample points; n = the number of sample points inside ICs; T = total carbon dioxide emissions inside ICs (tons); d = binary indicator variable equal to one if the point was deforested between 2001 and 2013; A = AGB circa 2000 (tons per hectare); and 100 = a scaling factor that converts sample points to total hectares.

We use a similar procedure to estimate carbon emissions on counterfactual land. Counterfactual land is represented by matched control points identified via nearest neighbor one-to-one propensity score matching. Our calculation takes into account the number of times each sample point is used as a match for a point inside ICs. That is, we estimate

$$C = \sum_{i}^{m} (w_i d_i \times A_i) \times 100$$

where m = the number of matched control points; C = total carbon dioxide emissions on counterfactual land (tons); and w = the number of times each matched point is used as a match.

Hence, we estimate *avoided* forest carbon emissions as T – C.

4.3. Sample

A limiting factor in defining our study area was the availability of spatial data on IC boundaries, which have not always been publicly available. We leveraged the efforts of LandMark, a global platform of indigenous and community lands led by World Resources Institute and the Rights and Resources Initiative. LandMark engaged in an ongoing effort to compile and disseminate these data (LandMark, 2016). Our study area is the Amazon regions of Bolivia, Brazil, Colombia and Ecuador, four countries for which LandMark had secured data on IC boundaries when our study began in 2015 (Fig. 1). For Brazil, the definition of the Amazon region has a legal foundation (INPE-DPI, 2016). For Bolivia, Colombia and Ecuador, it is defined by a map of the Amazon watershed (Mayorga et al., 2012).

We select a quasi-random sample of points in this study area by overlaying a rectangular 1 km sampling grid—that is, a grid with points spaced 1 km apart vertically and horizontally. We include in the sample all points where gridlines cross. We drop from the sample two subsamples. First, we drop all points inside protected areas, to avoid conflating the effects of ICs and of protected areas. Second, we drop a small number of points for which data from the various GIS layers are missing.

4.4. Variables

Table 2 lists the data used in our matching analysis, including the sources and units. Our deforestation data are derived from Hansen et al. (2013) and updates, a data set covering the global tropics that maps forest loss each year from 2001 to 2013 at a scale of 30 m × 30 m. Shapefiles for local communities were compiled for the LandMark web tool (LandMark, 2016). We use a variety of data to control for confounding factors: altitude, slope, directional orientation, the percent of each pixel with forest cover in 2000, the distance from each point to the nearest cleared sample point in 2000, biomass density circa 2000, travel time to large population centers circa 2000, population density circa 2000, opportunity cost of retaining forest cover, 50-year average precipitation, 50-year average temperature, and biome (Table 2).[7] The opportunity cost variable is average per hectare gross agricultural revenue (i.e., the forgone revenue when forest is left standing) estimated by Naidoo and Iwamura (2007) at a 5 min (9 km^2) scale using spatial information on crop productivity, livestock density and prices. To our knowledge, it is the only spatially explicit data on opportunity costs available for all four of our study countries.

5. Results

5.1. Bolivia

In Bolivia, as in all four of our study countries, IC points have different average characteristics than non-IC points: they tend to be at lower altitude, flatter, more forested, more carbon dense, farther from clearing and from large population centers, less populated and in areas with relatively low opportunity costs, more rain and higher temperatures (Table 3). However, our matching estimators do a reasonably good job of controlling for these differences. MSB after matching ranges from 4.1 to 4.2% versus 31.4% before (Table 4).

ATTs from all three of our matching estimators are statistically significant at the 1% level. They range from −2.3 to −3.6 percentage points over our 2001–2013 study period, which translates into 43 to 67% reductions below the counterfactual rate of deforestation—that is, the rate for matched control points (Table 4). Fig. 2 presents ATTs for all four study countries, focusing on estimates from the nearest neighbor 1–1 estimator. These results are robust to moderate levels of unobserved heterogeneity: for all of our matching estimators, Γ^* is 3.0 (Table 4).

Finally, we estimate that in Bolivia, ICs avoid 13 MMT of forest carbon emissions annually, a 77% reduction compared with estimated counterfactual emissions of 16 MMT (Table 5). These avoided carbon emissions represent 9% of Bolivia's total 2014 carbon emissions.

5.2. Brazil

In Brazil, our matching estimators do a good job of controlling for differences in land characteristics that affect our outcomes (Tables 3 and 4). MSB after matching is 4.5%, versus 48.9% before matching. ATTs from all three of our matching estimators are statistically significant at the 1% level. They range from −2.7 to −4.9 percentage points over our 2001–2013 study period, which translates into 49 to 88% reductions below the counterfactual rate of deforestation (Table 4, Fig. 2). These results are quite robust to unobserved heterogeneity: Γ^* ranges from 10.8 to 13.6.

We estimate that in Brazil, ICs avoid 184 MMT of forest carbon emissions annually, a 90% reduction compared with estimated counterfactual emissions of 205 MMT (Table 5). These avoided carbon emissions represent 14% Brazil's total 2014 carbon emissions.

[7] Note that the population density variable is dropped from the matching analysis for Bolivia, Ecuador and Colombia in order to avoid non-convergence.

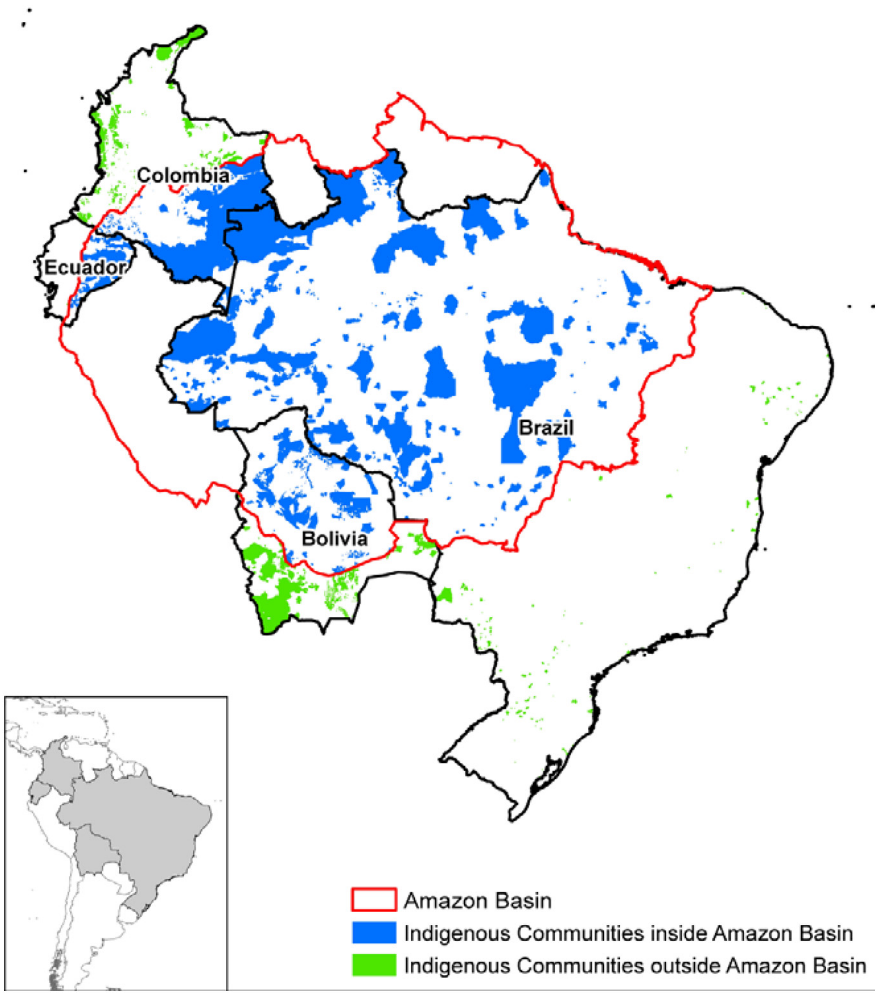

Fig. 1. Study area.

5.3. Colombia

For Colombia, once again, our matching estimators do a reasonably good job of controlling for differences in land characteristics that affect our outcomes (Tables 3 and 4). MSB after matching is 4.3 to 4.5%, versus 56.3% before. ATTs from two of our three estimators are statistically significant at the 5% level. They range from −0.0 to −0.8 percentage points over our 2001–2013 study period, which translates

Table 2
Variables used in matching analysis.

Variable	Description	Source	Units
Outcome			
Clear	Cleared during 2001–2013?	Hansen et al. (2013)	0/1
Treatment			
IC	Located in indigenous community (IC)?	LandMark (2016)	0/1
Control			
Altitude	Elevation	Farr et al. (2007)	m
Slope	Slope (100 ∗ tan(π angle/180))	Farr et al. (2007)	%
Northface	Aspect = N, NW or NE	Farr et al. (2007)	0/1
Perecent forest	Percent pixel forest in year 2000	Hansen et al. (2013)	%
Distance clearing	Distance nearest cleared pixel in year 2000	Hansen et al. (2013)	m
Carbon	Above-ground biomass density circa 2000	Saatchi et al. (2011)	mg/ha
Travel time	Time to nearest city w/pop. > 50 K circa 2000	Nelson (2008)	min
Population	Population density circa 2000	CIESIN-CIAT (2005)	person/ha
Opportunity cost[a]	Gross potential agricultural revenue	Naidoo and Iwamura (2007)	US $/ha
Rainfall	50-year average monthly precipitation	Hijmans et al. (2005)	mm
Temperature	50-year average monthly temperature	Hijmans et al. (2005)	°C
Biome	Terrestrial biome (forest, grassland, etc.)	Olson et al. (2001)	n/a
Protected	Protected area	WCU-UNEP (2007)	n/a
Amazon	Amazon region	INE-DPI (2016); Mayorga et al. (2012)	n/a

[a] Average per hectare gross agricultural revenue at 5 min (9 km^2) scale using spatial information on crop productivity, livestock density and prices.

Table 3
Variable means and difference-in-means tests for indigenous community (IC) and non-IC subsamples, by country.

Variable	Bolivia			Brazil			Colombia			Ecuador		
	Mean IC = 1 (*n* = 90,782)	Mean IC = 0 (*n* = 513,432)	*t*-Test	Mean IC = 1 (*n* = 1,105,080)	Mean IC = 0 (*n* = 2,873,689)	*t*-Test	Mean IC = 1 (*n* = 224,450)	Mean IC = 0 (*n* = 174,669)	*t*-Test	Mean IC = 1 (*n* = 50,954)	Mean IC = 0 (*n* = 54,287)	*t*-Test
Outcome												
Clear	0.018	0.053	***	0.007	0.086	***	0.004	0.050	***	0.020	0.022	***
Treatment												
IC	1.000	0.000	***	1.000	0.000	***	1.000	0.000	***	1.000	0.000	***
Controls												
Altitude	495.524	683.875	***	233.021	209.3467	***	173.287	402.412	***	534.355	1818.823	***
Slope	3.639	5.432	***	3.560	2.822	***	2.268	4.445	***	6.432	14.249	***
Northface	0.387	0.383	***	0.380	0.381	**	0.364	0.346	***	0.369	0.360	***
Perc. forest	78.691	56.985	***	91.303	67.978	***	95.884	81.795	***	96.307	69.024	***
Dist. clear.	5438.247	2952.140	***	12,684.300	4353.152	***	10,643.680	5529.391	***	7253.101	2762.691	***
Carbon	174.988	116.612	***	226.749	146.229	***	229.772	192.314	***	267.495	164.335	***
Travel time	815.813	636.678	***	2255.391	1014.377	***	3384.241	1525.130	***	1014.502	701.622	***
Population	3.401	10.238	***	1.050	4.828	***	0.747	6.829	***	4.398	41.071	***
Opp. cost	6.247	14.934	***	13.824	32.319	***	3.264	8.578	***	17.660	51.778	***
Rainfall	123.953	118.700	***	187.916	167.152	***	248.533	228.742	***	259.314	175.046	***
Temperature	242.511	234.947	***	255.186	257.550	***	263.688	253.666	***	238.525	176.965	***

*** $p < 1\%$.
** $p < 5\%$.

Table 4
Effect of indigenous community (IC) management on 2001–2013 deforestation inside IC borders: Average treatment effect on treated in percentage points, by estimator[a] [mean standardized bias[b]] {critical value of Rosenbaum's Γ[c]}.

Estimator	Bolivia		Brazil		Colombia		Ecuador	
	Percentage point change	% change	Percentage point change	% change	Percentage point change	% change	Percentage point change	% change
Naïve								
Unmatched controls	−3.5*** [31.4]	−66.4	−7.9*** [48.9]	−92.3	−4.6*** [56.3]	−91.3	−0.2* [87.9]	−7.3
Propensity score matching								
Nearest neighbor 1–1	−3.6*** [4.2] {3.0}	−67.3	−4.8*** [4.5] {10.8}	−87.9	−0.8** [4.3] {5.2}	−65.9	−0.5 [5.3] {1.4}	−21.3
Nearest neighbor 1–8	−3.6*** [4.1] {3.0}	−67.2	−4.9*** [4.5] {13.6}	−87.9	−0.8** [4.5] {9.2}	−65.5	−0.6 [6.2] {1.2}	−18.5
Probit w/matched controls	−2.3*** [4.1]	−42.6	−2.7*** [4.5]	−48.6	−0.0 [4.5]	−3.1	−0.4 [6.2]	−14.3
Def. rate outside ICs	5.3		8.6		5.0		2.2	
Def. rate counterfactual[d]	5.4		5.5		1.2		2.7	
Def. rate inside ICs	1.8		0.7		4.3		2.0	
No. points	604,214		3,978,769		399,119		105,241	
No. points treatment	90,782		1,105,080		224,450		50,954	

*** $p < 1\%$.
** $p < 5\%$.
* $p < 10\%$.
[a] Standard errors for propensity score matching estimators are clustered at the county (*municipio*) level.
[b] For a given covariate, the standardized bias (SB) is the absolute value of the difference of means in the treated and matched untreated subsamples as a percentage of the square root of the average sample variance in both groups. We report the mean SB for all covariates.
[c] Critical value of odds of differential assignment to IC due to unobserved factors (i.e., value above which ATT is no longer statistically significant at 10 percent level).
[d] Average over three propensity score matching estimators.

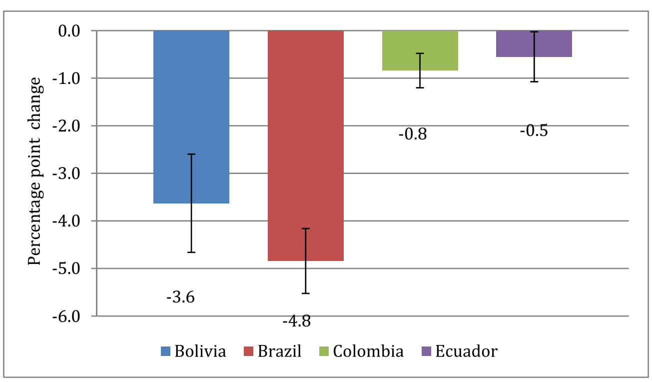

Fig. 2. Effect of indigenous community (IC) management on 2001–2013 deforestation, percentage point changes and standard errors, by country (nearest neighbor 1–1 matching model).

Table 5
Annual effect of indigenous community (IC) management on CO_2 emissions from clearing above-ground biomass.

Emissions	Bolivia	Brazil	Colombia	Ecuador
Inside ICs (MMT)	4	21	3	4
Counterfactual (MMT)	16	205	11	8
Avoided by ICs (MMT)	13	184	8	n/a[a]
Percentage reduction (%)	77	90	73	n/a[a]
Total country CO_2e 2014 (MMT)	134	1357	182	95
Percentage avoided (%)	9	14	4	n/a[a]

[a] Not estimated because we are unable to discern an effect of IC management on forest loss (Table 4).

into 3 to 67% reductions below the counterfactual rate of deforestation (Table 4, Fig. 2). These results are robust to unobserved heterogeneity: Γ* ranges from 5.2 to 9.2 (Table 4). That said, we note that our results for Colombia are less statistically and economically significant than for Bolivia and Brazil.

Finally, we estimate that ICs avoid 8 MMT of forest carbon emissions annually, a 73% reduction compared with estimated counterfactual emissions of 11 MMT (Table 5). These avoided carbon emissions represent 4% of Colombia's total 2014 carbon emissions.

5.4. Ecuador

In Ecuador, as in our other study countries, our matching estimators do a reasonably good job of controlling for differences in land characteristics that affect our outcomes (Tables 3 and 4). MSB after matching ranges from 5.3 to 6.2%, versus 87.9% before matching (Table 4). However, ATT estimates are considerably less significant, in both a statistical and an economic sense, than those for our three other study countries. None of the ATTs from our matching estimators are statistically significant. Moreover, point estimates are relatively small, ranging from −0.4 to −0.5 percentage points over our 2001–2013 study period, which translates into 14 to 21% reductions below the counterfactual rate of deforestation (Table 4, Fig. 2). These results are also less robust to unobserved heterogeneity than those for our other study countries: Γ* ranges from 1.2 to 1.4 (Table 4). Hence, we are not able to discern an effect of IC management on forest loss and therefore omit estimates of its effect on forest carbon emissions (Table 5).

6. Discussion

We have used fine-scale data on deforestation and above-ground biomass along with propensity score matching to measure the effect of IC management on deforestation and forest carbon emissions in the Amazon regions of Bolivia, Brazil, Colombia and Ecuador. Our analysis

has at least three significant limitations. First, matching does not control for unobserved confounding variables that could bias our results. We have used Rosenbaum bounds to test the sensitivity of our results to such bias. Second, we have not taken advantage of temporal variation in the titling of ICs and in forest loss to help to identify its effect. The reasons are discussed in Section 4.1. Finally, although our Hansen et al. (2013) outcome data are arguably the best globally available forest loss data, they have limitations (Burivalova et al., 2015; Tropek et al., 2014). For example, the data do not distinguish between forests and agroforests, and they measure deforestation only. Forest degradation from selective logging and other forms of disturbance may be an important a cause of environmental damage and carbon emissions in some parts of the Amazon.

Notwithstanding those limitations, we believe this analysis significantly advances our understanding of the environmental effects of IC management in general, and of such management in the Amazon specifically. It generates two broad sets of findings. First, the geophysical and socioeconomic characteristics of land inside ICs are clearly significantly different from those outside. As a result, it is important to control for these differences in estimating the deforestation effect of IC management. Second, after controlling for observable differences between IC and non-IC land, IC management is correlated with reduced deforestation and reduced forest carbon emissions in Bolivia, Brazil and Colombia. We are not able to discern an effect in Ecuador. Also, our results for Colombia are less statistically and economically significant than for Bolivia and Brazil.

What causal mechanisms drive these results? As discussed in Section 2, the treatment that we have analyzed—legally recognized IC management—has two components: IC management, and legal recognition of that management. Furthermore, several causal mechanisms (improved internal and external governances, additional interactions with external agents, etc.) plausibly link each component to reduced deforestation. Unfortunately, our data do not allow us to identify which of these components and mechanisms drive our results for each country. This is a fruitful area for future research. Additional research that leverages remotely sensed spatial panel data on forest cover change can help to identify the effect of titling separate from that of IC management (e.g., Ben Yishay et al., 2017; Blackman, 2018; Blackman et al., 2017; Buntaine et al., 2015; Hargrave and Kis-Katos, 2012). And more narrowly focused field research can help identify the causal mechanisms associated with titling.

What do our findings imply for policy? They suggest that policies that support existing legally recognized IC management can advance forest conservation and help combat climate change. Such policies might include providing the financial, technical, regulatory and political support ICs need to address threats to land rights from the expansion of commercial mining, energy exploitation and agriculture in the Amazon (Finer et al., 2008; Finer and Orta Martínez, 2010; Nepstad et al., 2008; Stocks, 2005). In addition, our results hint at but do not directly support the conclusion that titling ICs without formal land rights can advance forest conservation and climate policy. As noted above, we test the combined treatment of IC management and legal recognition of that management, and further research is needed to determine whether the second component by itself has significant effects.

Supporting IC management has the potential to advance climate policy in our study countries. As discussed in Section 3, in all four countries, LULUCF contributes a sizable share of the total greenhouse gas emissions (11 to 64%). The NDCs of three countries (Brazil, Colombia, and Ecuador) commit them to large overall reductions in GHGs in the next 10 to 20 years. And the NDCs of two countries (Bolivia and Brazil) commit them to zero illegal deforestation by 2020 or 2030. The extent to which IC management can be counted as contributions to meeting these formal commitments depends on the technicalities of emissions accounting—specifically, how NDC baselines for each commitment are defined, and relatedly, what additional forest conservation can be attributed to ICs, given those definitions. That said, our results suggest that legally recognized IC management at least has the potential to make such contributions.

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References

Aakvik, A., 2001. Bounding a matching estimator: the case of a Norwegian training program. Oxf. Bull. Econ. Stat. 63 (1), 115–143.
Abadie, A., Imbens, G., 2006. Large sample properties of matching estimators for average treatment effects. Econometrica 74 (1), 235–267.
Andam, K., Ferraro, P., Pfaff, A., Robalino, J., Sanchez, A., 2008. Measuring the effectiveness of protected-area networks in reducing deforestation. Proc. Natl. Acad. Sci. 105 (42), 16089–16094.
Baccini, A., Goetz, S., Walker, W., Laporte, N., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P., Dubayah, R., Friedl, M., Samanta, S., Houghton, R., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. Nat. Clim. Chang. 2, 182–185.
Barbier, E., Burgess, J., 2001. Tropical deforestation, tenure insecurity, and unsustainability. For. Sci. 47 (4), 497–509.
Ben Yishay, A., Heuser, S., Runfola, D., Trichler, R., 2017. Indigenous land rights and deforestation: evidence from the Brazilian Amazon. J. Environ. Econ. Manag. 86, 29–47.
Berkes, F., 1999. Sacred Ecology: Traditional Ecological Knowledge and Resource Management. Taylor and Francis, Philadelphia.
Berkes, F.J. Colding, Folke, C., 2000. Rediscorevery of traditional ecological knowledge as adaptive management. Ecol. Appl. 10, 1251–1262.
Blackman, A., 2013. Evaluating forest conservation policies in developing countries using remote sensing data: an introduction and practical guide. Forest Policy Econ. 34, 1–16.
Blackman, A., 2018. Does Titling Indigenous Communities Conserve Forests? Evidence From Bolivia. InterAmerican Development Bank, Washington, DC.
Blackman, A., Epanchin-Niell, R., Siikamäki, J., Velez-Lopez, D., 2014. Biodiversity Conservation in Latin America and the Caribbean: Prioritizing Policies. Resources for the Future Press, New York.
Blackman, A., Pfaff, A., Robalino, J., 2015. Paper park performance: Mexico's natural protected areas in the 1990s. Glob. Environ. Chang. 31, 50–61.
Blackman, A., Corral, L., Lima, E., Asner, G., 2017. Titling indigenous communities protects forests in the Peruvian Amazon. Proc. Natl. Acad. Sci. U. S. A. 114, 123–128.
Bromley, D., 1992. The commons, common property, and environmental policy. Environ. Resour. Econ. 2, 1–17.
Buntaine, M., Hamilton, S., Millones, M., 2015. Titling community land to prevent deforestation: an evaluation of a best-case program in Morona-Santiago, Ecuador. Glob. Environ. Chang. 33, 32–43.
Burivalova, Z., et al., 2015. Relevance of global forest change data set to local conservation: case study of forest degradation in Masoala National Park, Madagascar. Biotropica 47 (2), 267–274.
Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. J. Econ. Surv. 32, 31–72.
Center for International Earth Science Information Network (CIESIN), Columbia University, Centro Internacional de Agricultura Tropical (CIAT), 2005. Gridded Population of the World, Version 3 (GPWv3). Socioeconomic Data and Applications Center (SEDAC), Columbia University, Palisades, NY Available at. http://sedac.ciesin.columbia.edu/gpw (Accessed April 21, 2017).
Centro Internacional de Agricultura Tropical (CIAT), 2018. Climate Data Explorer (Available at:). http://www.wri.org/resources/data-sets/cait-historical-emissions-data-countries-us-states-unfccc.
Chomitz, K., 2007. At Loggerheads? Agricultural Expansion, Poverty Reduction and Environment in the Tropical Forests. World Bank, Washington, DC.
Clark, C., 2000. Land tenure delegitimation and social mobility in tropical Petén, Guatemala. Hum. Organ. 59 (4), 419–427.
de Sy, V., Herold, M., Achard, F., Beuchle, R., Clevers, J., Lindquist, E., Verchot, L., 2015. Land use patterns and related carbon losses following deforestation in South America. Environ. Res. Lett. 10 (12), 12404.
Ding, H., Veit, P., Gray, E., Reytar, K., Altamirano, J.-C., Blackman, A., Hodgdon, B., 2016. Climate Benefits, Tenure Costs: The Economic Case for Securing Indigenous Land Rights in the Amazon. World Resources Institute, Washington, DC.
Egger, P., Pfaffermayr, M., 2005. Estimating long run and short run effects in static panel models. Econ. Rev. 23 (3), 199–214.
Eisenstadt, T., West, K., 2017. Indigenous belief systems, science, and resource extraction: climate change attitudes in Ecuador and the Global South. Global Environ. Polit. 17 (1), 40–58.

Engel, S., López, R., 2008. Exploiting common resources with capital-intensive technologies: the role of external forces. Environ. Dev. Econ. 13 (5), 565–589.
Farr, T., et al., 2007. The shuttle radar topography mission. Rev. Geophys. 45.
Farzin, Y., 1984. The effect of the discount rate on depletion of exhaustible resources. J. Polit. Econ. 92, 841–851.
Finer, M., Orta Martínez, M., 2010. A second hydrocarbon boom threatens the Peruvian Amazon: trends, projections, and policy implications. Environ. Res. Lett. 5, 014012 (10pp).
Finer, M., Jenkins, C., Pimm, S., Keane, B., Ross, C., 2008. Oil and gas projects in the western Amazon: threats to wilderness, biodiversity, and indigenous peoples. PLoS One 3 (8), e2932. https://doi.org/10.1371/journal.pone.0002932.
Fogarty, D., 2014. The overlooked group of climate change fighter. In: Huffington Post, July 1. Available at. http://www.huffingtonpost.ca/david-fogarty/climate-change-indigenous_b_5637456.html (Accessed November 28, 2016).
Gregersen, H., El Lakany, H., Karsenty, A., White, A., 2010. Does the opportunity cost approach indicate the real cost of REDD + ? In: Rights and Realities of Paying for REDD + . Rights and Resources Initiative, Washington, DC.
Hansen, M., Potapov, P., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A., Thau, D., Stehman, S., Goetz, S., Loveland, T., Kommareddy, A., Egorov, A., Chini, L., Justice, C., Townshend, J., 2013. High-resolution global maps of 21st-century forest cover change. Science 342 (15 November), 850–853.
Hardin, G., 1968. The tragedy of the commons. Science 162, 1243–1248.
Hargrave, J., Kis-Katos, K., 2012. Economic causes of deforestation in the Brazilian Amazon: a panel data analysis for the 2000s. Environ. Resour. Econ. 54, 471–494.
Harris, N., Saatchi, S., Petrova, S., Salas, W., Hansen, M., Potapov, P., Lotsch, A., 2012. Baseline map of carbon emissions from deforestation in tropical regions. Science 336, 1573–1576.
Hayes, T., 2007. Does tenure matter? A comparative analysis of agricultural expansion in the Mosquitia forest corridor. Hum. Ecol. 35 (6), 733–747.
Hijmans, R., Cameron, S., Parra, J., Jones, P., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978.
Ho, D., Imai, K., King, G., Stuart, E., 2007. Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. Polit. Anal. 15, 199–236.
Houghton, R.A., House, J., Pongratz, J., et al., 2012. Carbon emissions from land use and land coverchange. Biogeosciences 9, 5125–5142.
Houthakker, H., 1965. New evidence on demand elasticities. Econometrica 33, 277–288.
Imbens, G., Wooldridge, J., 2009. Recent developments in the econometrics of program evaluation. J. Econ. Lit. 47 (11), 5–86.
Instituto Nacional de Pesquisas Espaciais-Divisão de Processamento de Imagens (INPE-DPI), 2016. Brazilian Legal Amazon Shape Files. Ambdata. Available at. http://www.dpi.inpe.br/Ambdata/English/extent_scale.php (Accessed December 16, 2016).
Johnson, C., Forsyth, T., 2002. In the eyes of the state: negotiating a ‘rights-based approach’ to forest conservation in Thailand. World Dev. 30 (9), 1591–1605.
Kahn, B., 2014. Indigenous rights to forest catch more carbon. Sci. Am.(August 5) Available at: https://www.scientificamerican.com/article/indigenous-rights-to-forests-catch-more-carbon (Accessed November 28, 2016).
LandMark, 2016. Global platform of indigenous and community lands. Available at: www.landmarkmap.org (Accessed December 7, 2016).
Larrea-Gallegos, G., Vázquez-Rowe, I., Gallice, G., 2017. Life cycle assessment of the construction of an unpaved road in an undisturbed tropical rainforest area in the vicinity of Manu National Park, Peru. Int. J. Life Cycle Assess. 22 (7), 1109–1124.
Liscow, Z., 2013. Do property rights promote investment but cause deforestation? Quasi-experimental evidence from Nicaragua. J. Environ. Econ. Manag. 65 (2), 241–261.
Mantel, N., Haenszel, W., 1959. Statistical aspects of the analysis of data from retrospective studies of disease. J. Natl. Cancer Inst. 22 (4), 719–748.
Mayorga, E., Logsdon, M., Ballester, M., Richey, J., 2012. LBA-ECO CD-06 Amazon River Basin (Geospatial Data Set). Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, TN Available at. http://daac.ornl.gov (Accessed November 28, 2016).
Mendelsohn, R., 1994. Property rights and tropical deforestation. Oxf. Econ. Pap. 46, 750–756.
Mesoamerican Alliance of Peoples and Forests (MAPF), 2015. Tropical forest carbon in indigenous territories: a global analysis. Available at. http://www.alianzamesoamericana.org/wp-content/uploads/2015/11/Tropical-Forest-Carbon-in-Indigenous-Territories-A-Global-Analysis.pdf (Accessed November 28, 2016).
Millennium Ecosystem Assessment (MEA), 2005. Ecosystems and Human Well-Being: Synthesis. Island Press, Washington, DC.
Muller, R., et al., 2012. Proximate causes of deforestation in the Bolivian lowlands: an analysis of spatial dynamics. Reg. Environ. Chang. 12, 445–459.
Naidoo, R., Iwamura, T., 2007. Global-scale mapping of economic benefits from agricultural lands: implications for conservation priorities. Biol. Conserv. 140, 40–49.
Nelson, A., 2008. Estimated Travel Time to the Nearest City of 50,000 or More People in Year. Global Environment Monitoring Unit, Joint Research Centre of the European Commission, Ispra, Italy, pp. 2000.
Nelson, A., Chomitz, K., 2011. Effectiveness of strict vs. multiple use protected areas in reducing tropical forest fires: a global analysis using matching methods. PLoS One 6 (8), e22722.
Nelson, G., Harris, V., Stone, S., 2001. Deforestation, land use, and property rights: empirical evidence from Darién, Panama. Land Econ. 77 (2), 187–205.
Nepstad, D., Schwartzman, S., Bamberger, B., Santilli, M., Ray, D., Schlesinger, P., Lefebvre, P., Alencar, A., Prinz, E., Fiske, G., Rolla, A., 2006. Inhibition of Amazon deforestation and fire by parks and indigenous lands. Conserv. Biol. 20 (1), 65–73.
Nepstad, D., Stickler, C., Soares-Filho, B., Merry, F., 2008. Philos. Trans. R. Soc. B 363, 1737–1746.
Nolte, C., Agrawal, A., Silvius, K.M., Soares-Filho, B.S., 2013. Governance regime and location influence avoided deforestation: success of protected areas in the Brazilian Amazon. Proc. Natl. Acad. Sci. 110 (13), 4956–4961.
Oliveira, J., 2008. Property rights, land conflicts and deforestation in the eastern Amazon. Forest Policy Econ. 10, 303–315.
Oliveira, P., Asner, G., Knapp, D., Almeyda, A., Galvan-Gildemeister, R., Keene, S., Raybin, R., Smith, R., 2007. Land-use allocation protects the Peruvian Amazon. Science 317, 1233–1236.
Olson, D.M., et al., 2001. Terrestrial ecoregions of the world: a new map of life on earth. Bioscience 51 (11), 933–938.
Ortiga, R., 2004. Models for Recognizing Indigenous Land Rights in Latin America. World Bank, Washington, DC.
Ostrom, E., 1990. Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge University Press, Cambridge.
Paris Agreement, 2016. United Nations Treaty Collection. 8 July. Available at. http://unfccc.int/files/home/application/pdf/paris_agreement.pdf (Accessed November 28, 2016).
Penman, J., Gytarsky, M., Hiraishi, T., et al., 2003. Good Practice Guidance for Land Use, Land-Use Change and Forestry. Institute for Global Environmental Strategies Available at. http://www.ipcc-nggip.iges.or.jp/public/gpglulucf/gpglulucf_contents.html (Accessed December 7, 2016).
Persha, L., Agrawal, A., Chhatre, A., 2011. Social and ecological synergy: local rule-making, forest livelihoods, and biodiversity conservation. Science 331, 1606–1608.
Pfaff, A., Robalino, J., Lima, E., Sandoval, C., Herrera, L.D., 2014. Governance, location and avoided deforestation from protected areas: greater restrictions can have lower impact, due to differences in location. World Dev. 55, 7–20.
Popkin, G., 2015. Indigenous people could be key to storing carbon in tropical forests, new report concludes. Sci. Insider. https://doi.org/10.1126/science.aad7506. Available at: http://www.sciencemag.org/news/2015/12/indigenous-people-could-be-key-storing-carbon-tropical-forests-new-report-concludes (Accessed November 28, 2016).
Ramankutty, N., Gibbs, H., Achard, F., DeFries, R., Foley, J., Houghton, R., 2007. Challenges to estimating carbon emissions from tropical deforestation. Glob. Chang. Biol. 13, 51–66.
Ribot, J., Agrawal, A., Larson, A., 2006. Recentralizing while decentralizing: how national government reappropriate forest resources. World Dev. 34 (11), 1864–1886.
Rosenbaum, P., 2002. Observational Studies, 2nd ed. Springer, New York.
Rosenbaum, P., Rubin, D., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.
Rustagi, D., Engel, S., Kosfeld, M., 2010. Conditional cooperation and costly monitoring explain success in forest commons management. Science 330 (6006), 961–965.
Saatchi, S., Harris, N., Brown, S., Lefsky, M., Mitchard, E., Salas, W., Zutta, B., Buermann, W., Lewis, S., Hagen, S., Petrovac, S., White, L., Silmani, M., Morel, A., 2011. Benchmark map of forest carbon stocks in tropical regions across three continents. Proc. Natl. Acad. Sci. 108 (24), 9899–9904.
Schroeder, H., 2010. Agency in international climate negotiations: the case of indigenous peoples and avoided deforestation. Int. Environ. Agreements 10, 317–332.
Schwartzman, S., Zimmerman, B., 2005. Conservation alliances with indigenous peoples of the Amazon. Conserv. Biol. 19 (3), 721–727.
Seymour, F., Busch, J., 2016. Why Forests? Why Now? The Science, Economics and Politics of Tropical Forests and Climate Change. Center for Global Development, Washington, DC.
Sheil, D., Boissiere, M., Beudoin, G., 2015. Unseen sentinels: local monitoring and control in conservation's blind spots. Ecol. Soc. 20 (2), 39.
Stevens, C., Winterbottom, R., Springer, J., Reytar, K., 2014. Securing Rights, Combating Climate Change: How Strengthening Community Forest Rights Mitigates Climate Change. World Resources Institute, Washington, DC.
Stocks, A., 2005. Too much for too few: problems of indigenous land rights in Latin America. Annu. Rev. Anthropol. 34 (1), 85–104.
Stuart, E., 2010. Matching methods for causal inference: a review and a look forward. Stat. Sci. 25 (1), 1–21.
Toledo, V., 2001. Indigenous peoples and biodiversity. In: Levin, S. (Ed.), Encyclopedia of Biodiversity. Academic Press, Cambridge, MA.
Tropek, R., et al., 2014. Comment on ‘high-resolution global maps of 21st-century forest cover change. Science 344, 981.
van der Werf, G., Morto, D., DeFries, R., Olivier, J., Kasibhatla, P., Jackson, R., Collatz, G., Randerson, J., 2009. CO_2 emissions from forest loss. Nat. Geosci. 2, 737–738.
Vergara-Aseno, G., Potvin, C., 2014. Forest protection and tenure status: the key role of indigenous peoples and protected areas in Panama. Glob. Environ. Chang. 28, 205–215.
Wallbott, L., 2014. Indigenous peoples in UN REDD + negotiations: “importing power” and lobbying for rights through discursive interplay management. Ecol. Soc. 19 (1), 21. https://doi.org/10.5751/ES-06111-190121 (Accessed November 28, 2016).
World Bank, 2015. Indigenous Latin America in the Twenty-First Century. World Bank, Washington, DC.
World Bank, 2018. World development indicators (Available at:). http://wdi.worldbank.org/table/2.1. http://wdi.worldbank.org/table/3.1.
World Conservation Union and UNEP–World Conservation Monitoring Centre (WCU-UNEP), 2007. World Database on Protected Areas, Version 2007. WCMC, Cambridge.
Wunder, S., 2005. Payments for Environmental Services: Some Nuts and Bolts (Occasional Paper No. 42). Center for International Forestry Research, Bogor.
Zarin, D., Harris, N., Baccini, A., Aksenov, D., Hansen, M., Ramos, C., Azevedo, T., Margono, B., Alencar, A., Gabris, C., Allegretti, A., Potapov, P., Farina, M., Walker, W., Shevade, V., Loboda, T., Turubanova, S., Tyukavina, A., 2015. Can carbon emissions from tropical deforestation drop by 50% in five years? Glob. Chang. Biol. 22 (4), 1336–1347.